An Intelligent Vision System for Product Label and Banknote Recognition for Visually Impaired Assistance

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Abstract

Visual impairment significantly limits individuals' ability to independently perform daily tasks such as identifying banknotes and reading product labels, leading to potential errors in financial transactions and reduced accessibility to essential information. This study proposes an intelligent vision-based assistive system that integrates barcode detection with ORB (Oriented FAST and Rotated BRIEF) feature matching to enable accurate and real-time object recognition on mobile devices. The system captures images via a smartphone camera and provides audio feedback through a text-to-speech mechanism to support visually impaired users. Experimental results demonstrate that the proposed system achieves an overall recognition accuracy of 96.2%, with 94.6% for product labels and 97.8% for banknotes, along with an AUC of 0.97 and an average processing time of approximately 1.80 seconds. The system also exhibits balanced classification performance with high precision, recall, and F1-score values. A user evaluation involving 30 visually impaired participants confirms that the system improves task performance and usability, particularly with minimal training. These findings suggest that the proposed hybrid approach offers a robust, efficient, and practical solution for real-world assistive applications, thereby contributing to the development of intelligent technologies that enhance accessibility, support independent living, and align with the vision of a smart ageing society.

Keywords: Assistive Technology, Computer Vision, Barcode Detection, ORB Feature Matching, Visually Impaired, Smart Ageing Society

Background and Statement of the problem

Visual impairment is a significant challenge that affects an individual's ability to interact with their surroundings and perform daily activities independently. According to the World Health Organization (WHO, 2023), at least 2.2 billion people globally have a vision impairment or blindness, of which a significant proportion is preventable or remains unaddressed. Individuals with visual impairment often experience difficulties when identifying product information, reading labels, or recognizing banknotes during financial transactions. According to the Thailand Association of the Blind, many still rely on assistance from others when accessing product information or handling money, which can limit their independence and quality of life (Changsee, personal communication, 2024; Khadwong, personal communication, 2024).

To address these challenges, various assistive technologies have been developed using computer vision and mobile technologies. Mobile-based recognition systems, for example, allow users to capture images of objects and receive audio feedback describing the recognized information (Suriyaporn, 2018). However, many existing systems are designed to recognize only a single type of object, such as banknotes or text labels, which limits their practicality in everyday situations.

Several studies have explored barcode recognition techniques for product identification. Barcode detection has been widely applied in manufacturing and inventory management systems because of its reliability and structured data format (Chuchuay, 2017). In addition, mobile barcode readers have been developed to assist users in identifying consumer products by decoding barcode information captured through mobile cameras (Jetjarurat, 2013).

Image processing techniques have also been applied in assistive applications. For example, automated systems have been developed to identify pharmaceutical labels and related documentation to improve medication safety (Sriborrirak, 2018). Furthermore, pattern recognition and character recognition algorithms have been widely studied in computer vision to enhance the accuracy of visual recognition systems (Endo, 2012). These studies demonstrate the potential of image recognition technologies for improving accessibility.

Despite these developments, most existing approaches focus on a single recognition method or a single object category, which may limit their effectiveness in real-world assistive applications. In practical scenarios, users often encounter diverse objects under varying environmental conditions, such as changes in lighting, occlusion, and viewing angles. Relying on a single recognition technique may therefore reduce system robustness and lead to inconsistent performance. Furthermore, many existing systems are designed and evaluated under controlled conditions. This may not fully reflect real-world usage, where multiple object types must be recognized within a single interaction. In practice, users often need to identify multiple types of objects, including product labels and banknotes, using the same assistive tool. Therefore, there is a need for an integrated recognition approach that combines complementary techniques to improve accuracy, robustness, and practical usability in real-world environments.

Based on this motivation, this research proposes an intelligent vision-based recognition system that integrates barcode detection and ORB (Oriented FAST and Rotated BRIEF) feature matching techniques to recognize both product labels and Thai banknotes. The proposed system is designed to achieve high recognition accuracy while maintaining near real-time performance and usability on mobile devices, thereby supporting independent living and contributing to the development of assistive technologies for a smart ageing society.

Objective

The objectives of this research are as follows:

1. To design and develop an intelligent vision-based assistive system capable of recognizing product labels and Thai banknotes for visually impaired users.
2. To integrate barcode detection and ORB feature matching techniques for object recognition in mobile-based assistive applications.
3. To evaluate the performance of the proposed system in terms of recognition accuracy and classification performance using product label and banknote datasets.
4. To analyze the processing efficiency of the system by measuring the average processing time required for object recognition.
5. To conduct a user experiment with visually impaired participants to examine the usability of the proposed system and analyze task success rates during object recognition tasks.

Expected benefits

The expected benefits of this research are as follows:

1. Development of an assistive recognition system that enables visually impaired individuals to identify product labels and banknotes in daily life.
2. Enhancement of independence and accessibility through real-time audio-based object recognition on mobile devices.
3. Demonstration of a practical and efficient hybrid recognition approach by integrating barcode detection with ORB feature matching for mobile assistive applications.
4. Contribution to the development of intelligent assistive technologies that support independent living and improve quality of life for visually impaired individuals within a smart ageing society.

Literature Review

Recent advancements in computer vision and mobile technologies have significantly enhanced the development of assistive technologies designed to support visually impaired individuals. Numerous studies have focused on object recognition systems that enable users to identify objects through image processing combined with audio feedback mechanisms.

One of the fundamental approaches for assisting visually impaired users is barcode recognition. Jetjarurat (2013) developed a mobile barcode reader specifically for visually impaired individuals in Thailand, allowing users to capture barcode images via a smartphone camera and receive product information through audio output. Similarly, Chuchuay (2017) proposed an image-based barcode detection method for industrial product classification, demonstrating high reliability under controlled conditions. However, barcode-based approaches are highly dependent on barcode visibility and may fail in cases of occlusion, distortion, or damaged labels.

In parallel, image-based recognition techniques have been widely explored for assistive applications. Sriborrirak (2018) developed an automated system for identifying pharmaceutical labels to enhance medication safety, while Suriyaporn (2018) proposed a real-time mobile application for recognizing Thai banknotes. Although these systems achieved high accuracy, their performance is often sensitive to environmental variations such as lighting conditions and background noise.

Feature-based methods have also played a significant role in object recognition. Lowe (2004) introduced the Scale-Invariant Feature Transform (SIFT), followed by the Speeded-Up Robust Features (SURF) algorithm proposed by Bay et al. (2008), which improved computational efficiency. To further support real-time applications, Rublee et al. (2011) proposed the ORB (Oriented FAST and Rotated BRIEF) algorithm, which enables fast and efficient feature extraction and matching. Due to its low computational cost, ORB is particularly suitable for mobile-based assistive systems.

More recently, deep learning approaches have significantly advanced object recognition performance. Redmon et al. (2016) introduced the YOLO framework for real-time object detection, while He et al. (2016) proposed the ResNet architecture for improving classification accuracy. Despite their effectiveness, these approaches typically require large-scale datasets and high computational resources, which may limit their applicability in lightweight mobile environments.

In addition to recognition techniques, prior studies have emphasized the importance of system design and user-centered development in assistive technologies. Ngamsantivong (2006) highlighted the role of structured system design while proposing a model-driven development approach for flexible applications. User requirements have also been investigated through interviews with visually impaired individuals (Changsri, 2021; Khadwong, 2021), indicating that simplicity, accuracy, and real-time audio feedback are critical factors in assistive system adoption. Furthermore, Endo (2012) demonstrated that variation-based learning can improve recognition performance in noisy environments, reinforcing the importance of robustness in real-world applications.

Based on the reviewed literature, it is evident that most existing systems rely on a single recognition approach, such as barcode detection, OCR, or image-based classification. While these methods are effective in specific contexts, they often struggle to handle diverse real-world scenarios where multiple object types and varying environmental conditions are present. Moreover, existing solutions typically address either product identification or currency recognition independently, rather than providing a unified system.

Therefore, this study proposes a hybrid intelligent vision system that integrates ORB feature matching with barcode detection to enhance recognition accuracy, robustness, and real-time performance. Unlike previous approaches, the proposed system supports both product label and banknote recognition within a single mobile platform, addressing the practical needs of visually impaired users in everyday situations.

Conceptual Framework

The conceptual framework of this study is developed based on established research in assistive technologies, computer vision, and mobile object recognition systems. Vision-based assistive systems have been shown to significantly improve accessibility for visually impaired users by enabling automatic object recognition and auditory feedback (Jetjarurat, 2013; Suriyaporn, 2018). Barcode recognition techniques are widely applied in product identification due to their reliability in decoding structured information (Chuchuay, 2017), while feature-based methods such as ORB (Oriented FAST and Rotated BRIEF) provide efficient and robust real-time recognition under varying conditions (Rublee et al., 2011; Endo, 2012). From a system design perspective, this study adopts the Input–Process–Output (IPO) model to represent the flow of data and system functionality (Laudon & Laudon, 2018).

Based on these foundations, this research proposes an integrated recognition framework that combines barcode detection and feature-based recognition to enhance object identification performance in real-world environments. The framework consists of three main components: input, processing, and output. The input component involves image acquisition using a mobile device camera. The captured image is then processed through image preprocessing, barcode detection, and ORB feature matching to support accurate object recognition.

From a conceptual perspective, the framework explicitly represents the relationship between key system components. Image Acquisition serves as the input stage, followed by Image Processing, which enhances image quality and prepares data for analysis (Gonzalez & Woods, 2018). The processed data is then passed to the Object Recognition stage, where barcode detection and ORB feature matching are applied. The results are delivered through the output stage as Audio Feedback using a text-to-speech module, aligning with assistive interaction principles for visually impaired users (Stephanidis, 2019). These components operate as an integrated pipeline that transforms visual input into meaningful auditory information in near real-time.

To support systematic evaluation, key variables are defined in terms of both technical performance and usability. Recognition Accuracy, Precision, Recall, and F1 -score are used to evaluate classification performance (Sokolova & Lapalme, 2009), while Processing Time measures system efficiency. User Task Success Rate is used to assess usability in real-user experiments. This framework forms the foundation for the system development and experimental design presented in the methodology section, and is illustrated in Figure 1.

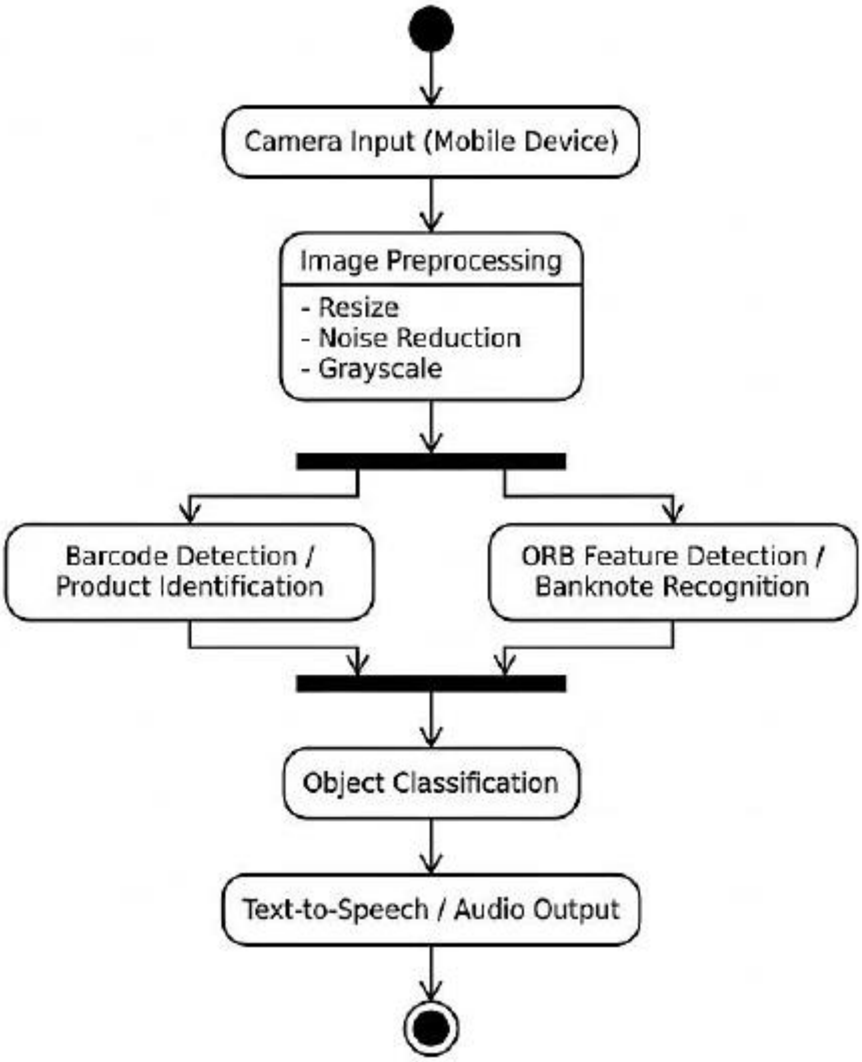

Figure 1 Conceptual Framework of the Proposed Assistive Recognition System

Research Methodology

This study presents the development and evaluation of an intelligent vision-based recognition system designed to assist visually impaired users in identifying product labels and Thai banknotes. The methodology consists of four main stages: dataset preparation, barcode detection, ORB feature matching, and system performance evaluation.

1. Dataset Preparation

A dataset was constructed using images collected from real-world environments such as supermarkets and convenience stores, following prior assistive product identification studies (Jetjarurat, 2013). The dataset consists of two categories: product labels and Thai banknotes.

For product recognition, 300 types of product labels were collected, resulting in 3,427 images captured under varying lighting conditions, orientations, and packaging materials. As shown in Figure 2, each label includes key attributes such as product name, barcode, and expiration date. For banknote recognition, five Thai denominations (20, 50, 100, 500, and 1,000 Baht) were used, as illustrated in Figure 3, with a total of 500 images captured under different viewing conditions.

(a) Product name (b) Barcode information (c) expiration date characters

Figure 2 Product label contains

(a) Example of a 20-Baht banknote (b) Example of a 50-Baht banknote

(c) Example of a 100-Baht banknote (d) Example of a 500-Baht banknote

(e) Example of a 20-Baht banknote

Figure 3 Examples of Thai banknotes used in the dataset

The dataset was divided into training and testing sets using an 80:20 split. The training set was used to construct the reference feature database, while the testing set was used for performance evaluation. Data augmentation techniques, including rotation, brightness adjustment, and scaling, were applied to improve robustness. A summary of the dataset is presented in Table 1.

Table 1 Dataset Description

Dataset Category	Number of Classes	Total Images	Training Images (80%)	Testing Images (20%)	Description
Product Labels	300 types	3,427	2,742	685	Images of product packaging collected from supermarkets and convenience stores under different lighting conditions and viewing angles
Thai Banknotes	5 types	500	400	100	Images of Thai currency denominations (20, 50, 100, 500, 1,000 Baht) captured using a mobile camera
Total	305	3,927	3,142	785	Combined dataset used for training and evaluation

2. Barcode Detection

Barcode detection is applied as the first stage of product identification due to its reliability in extracting structured product information (Chuchuay, 2017). The implementation was conducted using the pyzbar library in Python.

The barcode detection process, illustrated in Figure 4 and Figure 5, includes grayscale conversion, edge enhancement, noise reduction, thresholding, morphological operations, and contour detection to localize barcode regions. Once detected, barcode information is decoded and matched with the product database. If barcode detection fails due to occlusion, poor image quality, or the absence of barcode patterns, the system proceeds to feature-based recognition.

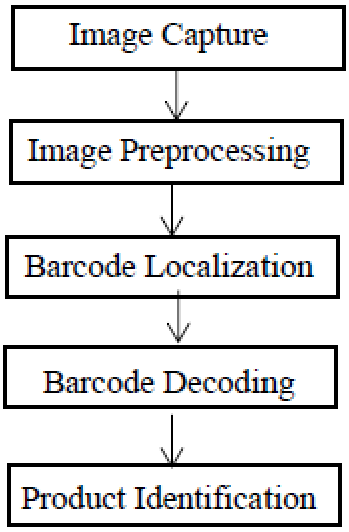

Figure 4 Barcode Detection Process

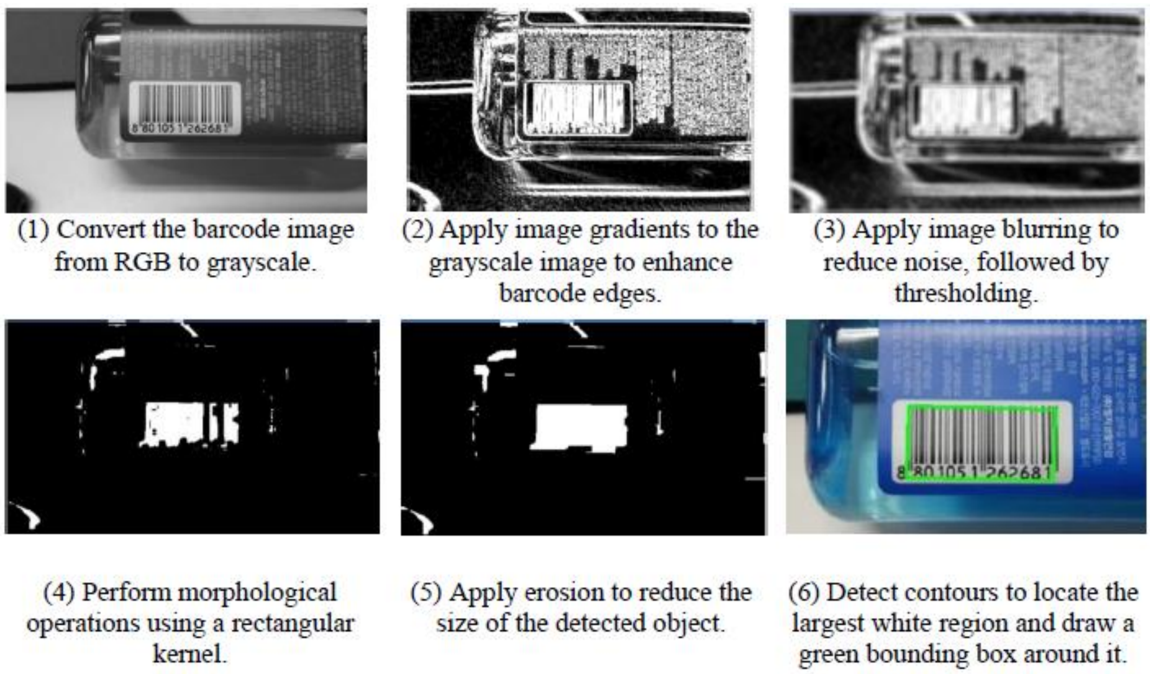

Figure 5 Barcode detection process consisting of six processing steps

3. ORB Feature Matching

When barcode detection is unsuccessful, ORB (Oriented FAST and Rotated BRIEF) feature matching is applied for object recognition. The overall process is shown in Figure 6, with classification examples presented in Figure 7. ORB combines the FAST keypoint detector and BRIEF descriptor to extract distinctive features, which are matched against a reference database using Hamming distance (Rublee et al., 2011; Endo, 2012).

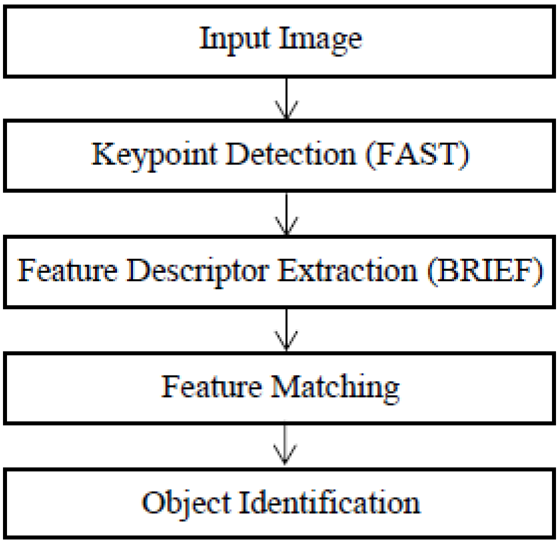

Figure 6 ORB Feature Matching

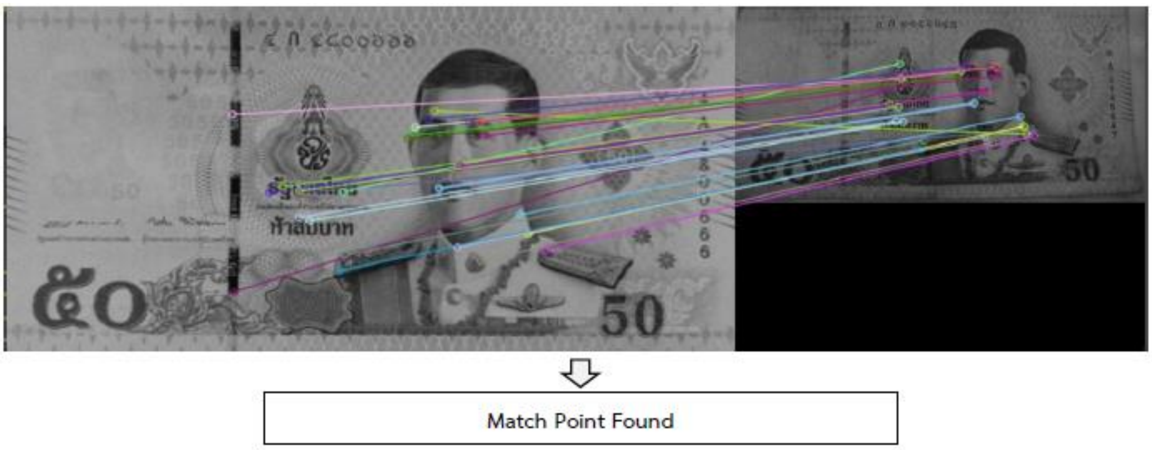

Figure 7 Example of Thai Banknote Classification.

4. Algorithm Formulation

This section describes the mathematical formulation used in the object recognition process, including ORB feature extraction and similarity matching.

4.1 ORB Feature Detection

The ORB algorithm combines the FAST keypoint detector and the BRIEF descriptor to extract distinctive features from images. The FAST detector identifies corner points in an image by evaluating the intensity differences between a candidate pixel and its surrounding pixels.

A pixel pis classified as a keypoint if the intensity difference between the center pixel and surrounding pixels exceeds a predefined threshold t.

$$|I(p) - I(p_i)| > t$$

where *I(p)* is the intensity of the center pixel, $I(p_i)$is the intensity of surrounding pixels and t is the intensity thresh old.

4.2 Feature Descriptor Matching

After feature extraction, the similarity between descriptors from the captured image and reference images is calculated using the Hamming distance.

$$D_H(x, y) = \sum_{i=1}^{n} x_i \oplus y_i$$

where x *and* y represent binary feature descriptors, $\oplus$ denotes the XOR operation and n is the descriptor length.A match is considered valid when the Hamming distance is below a predefined threshold.

4.3 Recognition Decision

The final recognition decision is determined by selecting the reference object that produces the highest number of valid feature matches.

$$R = \arg\max_i (M_i)$$

where M_i is the number of matched features for the object i, R represents the recognized object.

5. System Implementation and Experimental Setup

The proposed system was implemented using Python on a mobile-based platform. Experiments were conducted on a smartphone device running the Android operating system, with image processing and recognition implemented using OpenCV and pyzbar libraries.

6. Performance Evaluation

The system performance was evaluated using both quantitative metrics and user-based evaluation. Recognition Accuracy was calculated based on True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). In addition, Precision, Recall, and F1-score were used to evaluate classification performance, supported by confusion matrix analysis (Sokolova & Lapalme, 2009). Processing Time was also measured to assess system efficiency in real-time usage.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

7. User Experiment and Ethical Considerations

A user study was conducted with 30 visually impaired participants to evaluate system usability and task performance. Participants were recruited using purposive sampling from a visually impaired community group. All participants provided informed consent prior to the experiment, and the study followed standard ethical guidelines for human-centered research.

During the experiment, participants performed object recognition tasks using the proposed system. User Task Success Rate was measured to evaluate usability and effectiveness in real-world scenarios.

This methodology aligns with the conceptual framework by integrating image acquisition, processing, object recognition, and audio feedback into a unified evaluation pipeline.

Research Results

The proposed intelligent vision system was comprehensively evaluated through both quantitative performance analysis and real-user experiments. The evaluation framework consists of seven key aspects: (1) system interface demonstration, (2) recognition accuracy, (3) product label recognition performance, (4) confusion matrix and classification metrics, (5) ROC curve analysis, (6) processing time evaluation, (7) user evaluation, and (8) comparison with existing methods.

1. **System Interface and Operation**

The user interface of the proposed assistive recognition system is illustrated in Figure 8. The system was designed with accessibility as a primary consideration, providing a simple and intuitive interface tailored for visually impaired users.

(a) Login screen (b) System function interface

(c) Simulation of product label and Thai banknote scanning.

Figure 8 User interface of the proposed assistive recognition system

The interface supports real-time camera input and provides audio feedback following recognition, thereby enabling effective user interaction.

2. Recognition Accuracy

The recognition accuracy of the proposed system was evaluated using a dataset consisting of product labels and Thai banknotes captured under diverse environmental conditions.

As presented in Table 2, the proposed system achieved an overall accuracy of 96.2%, with 94.6% for product labels and 97.8% for banknotes. The higher accuracy observed in banknote recognition can be attributed to the more distinctive visual features and standardized structure of currency images, compared to the variability in product packaging.

Table 2 Recognition Accuracy Results

Object Type	Accuracy
Product Labels	94.6%
Banknotes	97.8%
Overall Accuracy	96.2%

These results highlight the effectiveness of the hybrid approach, where barcode detection provides reliable identification when structured information is available, while ORB feature matching compensates in cases where barcode detection fails. This complementary mechanism significantly improves robustness in real-world scenarios compared to single-method approaches.

3. Product Label Recognition Performance

The product label recognition module is based on barcode detection and decoding techniques. The evaluation results in Table 3 show that the system achieved a barcode detection rate of 97.8% and a decoding accuracy of 96.5%, resulting in an overall product recognition accuracy of 95.4%.

Table 3 Barcode Detection Performance

Metric	Value (%)
Barcode Detection Rate	97.8
Barcode Decoding Accuracy	96.5
Product Recognition Accuracy	95.4

These results indicate that the system maintains robust performance even under challenging conditions such as partial occlusion and varying illumination.

4. Confusion Matrix and Classification Metrics

To further analyze classification performance, a confusion matrix was constructed, as shown in Figure 9.

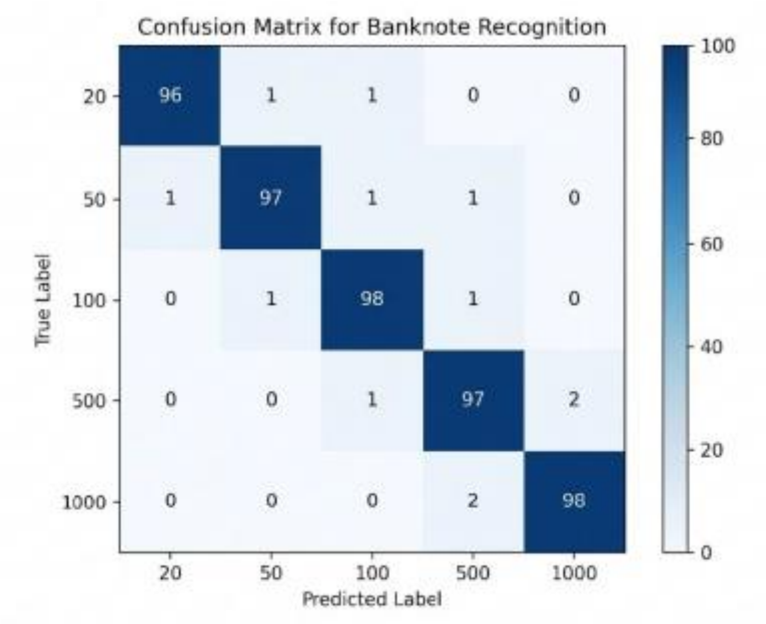

Figure 9 Confusion Matrix Heatmap (5 Classes: 20, 50, 100, 500, 1000 Baht)

The confusion matrix shown in Figure 9 indicates that most predictions are correctly classified, as reflected by strong diagonal values. Minor misclassifications are observed between 500 and 1000 Baht denominations, which can be attributed to visual similarities in color and partial occlusion during image capture.

This observation suggests that while ORB feature matching is robust to rotation and illumination variations, its performance may be affected when discriminative features are insufficiently distinctive. Similar limitations have been reported in feature-based recognition methods (Rublee et al., 2011). Nevertheless, the overall high precision (95.8%) and recall (96.4%) values presented in Table 4 indicate that the system maintains balanced performance with low false positive and false negative rates.

Table 4 Performance Metrics for Banknote Recognition

Banknote Denomination	Precision	Recall	F1-score
20 Baht	0.990	0.980	0.985
50 Baht	0.980	0.970	0.975
100 Baht	0.970	0.980	0.975
500 Baht	0.960	0.970	0.965
1000 Baht	0.980	0.980	0.980
Average	0.958	0.964	0.961

These results confirm that the proposed system achieves high classification reliability with balanced precision and recall performance.

5. ROC Curve Analysis

The Receiver Operating Characteristic (ROC) curve is illustrated in Figure 10. the system achieved an AUC of approximately 0.97, indicating excellent discriminative capability. The ROC curve demonstrates that the system maintains a high true positive rate across varying threshold levels while effectively controlling false positives.

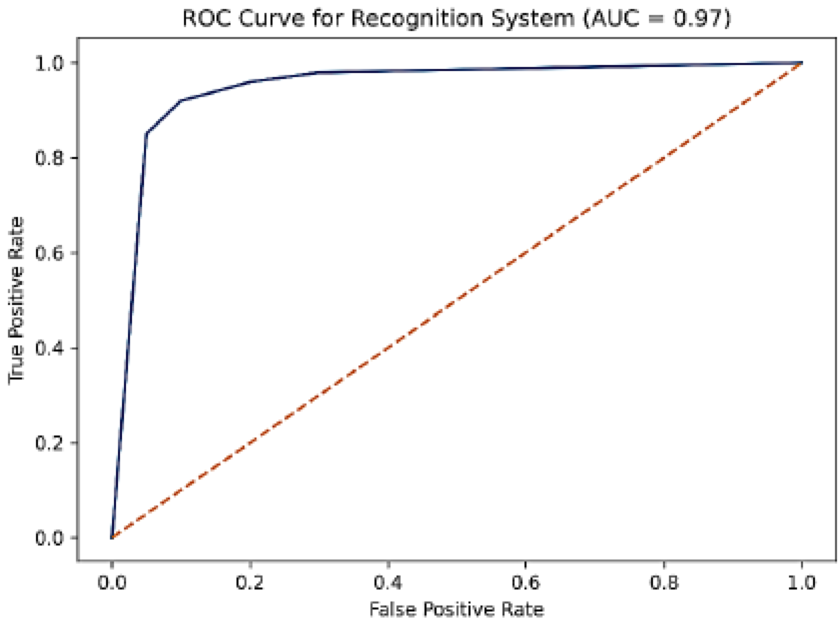

Figure 10 ROC Curve (AUC ≈ 0.97)

This result confirms that the proposed hybrid model provides stable classification performance under different decision thresholds, which is essential for real-world assistive applications where environmental conditions may vary dynamically.

6. Processing Time Evaluation

The processing time of the proposed system was evaluated to assess its efficiency for real-time applications. As shown in Table 5 and Figure 11, the system achieved an average processing time of 1.80 seconds, indicating near real-time performance. The slightly higher processing time for product labels (1.92 seconds) compared to banknotes (1.68 seconds) is likely due to the additional barcode detection and decoding steps.

Table 5 Processing Time Performance

Table 5 Processing Time Performance

Object Type	Average Processing Time
Product Labels	1.92 seconds
Banknotes	1.68 seconds
Average	1.80 seconds

The processing time performance is illustrated in Figure 11.

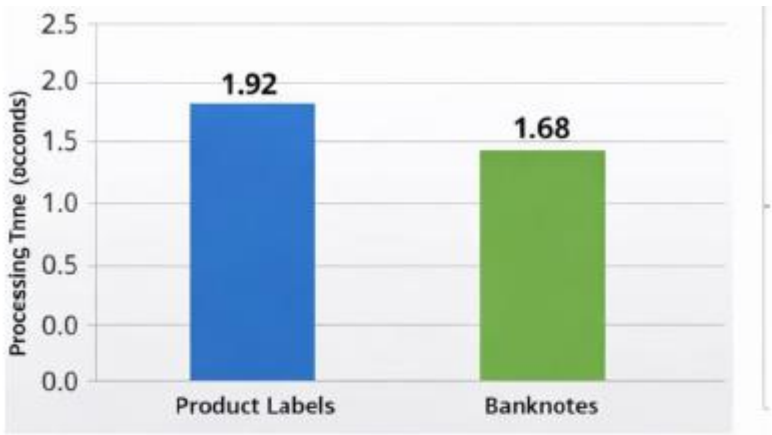

Figure 11 Processing Time Performance of the Proposed System

Despite this variation, the overall processing time remains within acceptable limits for assistive applications, where responsiveness is critical for user interaction. Compared to computationally intensive methods such as deep learning-based models, the proposed approach offers a more efficient solution suitable for mobile deployment.

7. User Evaluation

To evaluate the usability of the proposed recognition system, a user experiment was conducted with 30 visually impaired participants. The participants were divided into two groups based on their level of visual impairment:

- 15 participants with total blindness
- 15 participants with low vision

To analyze the effect of user training, each group was further divided into two subgroups: a trained group and an untrained group. The trained group received a brief introduction and demonstration before using the system, while the untrained group used the system without prior instruction.

The participant distribution is summarized in Table 6.

Table 6 Participant Distribution in User Evaluation

Participant Group	Trained	Untrained	Total
Totally Blind	8	7	15
Low Vision	7	8	15
Total	15	15	30

The results indicate that trained users performed more efficiently and interacted more effectively with the system compared to untrained users.

8. User Task Success Rate

The task success rate for each participant group is summarized in Table 7.

Table 7 User Task Success Rate

Group	Success Rate
Blind (Trained)	94%
Blind (Untrained)	86%
Low Vision (Trained)	96%
Low Vision (Untrained)	88%

The results in Table 7 indicate that trained users achieved higher task success rates (up to 96%) compared to untrained users (as low as 86%). This finding suggests that user familiarity plays a significant role in the effective utilization of assistive technologies.

The performance gap between trained and untrained groups highlights the importance of user-centered design and onboarding processes in assistive system deployment. These findings are consistent with prior studies emphasizing usability and interaction simplicity as key factors in assistive technology adoption (Stephanidis, 2019).

9. **Comparison with Existing Methods**

The performance of the proposed system was compared with existing approaches, as shown in Table 8., the proposed method achieves competitive accuracy (96.2%) compared to both classical and deep learning-based approaches. While deep learning models such as YOLO and ResNet report slightly higher accuracy, they require substantial computational resources and large-scale training datasets.

Table 8 Comparison with Previous Recognition Systems

Study	Method	Object Type	Accuracy	Key Limitation
Lowe (2004)	SIFT	General Objects	96.0%	High computational cost
Bay et al. (2008)	SURF	General Objects	95.5%	Still computationally intensive
Rublee et al. (2011)	ORB	ORB	95.8%	Less robust than SIFT in complex scenes
Endo (2012)	Feature Variation Model	Characters	91.8%	Limited generalization
Jetjarurat (2013)	Barcode Scanning	Product Labels	92.0%	Requires visible barcode
Redmon et al. (2016)	YOLO	Multi-object Detection	97.0%	Requires large training dataset
He et al. (2016)	ResNet	ResNet	97.5%	High computational resources
Chuchuay (2017)	Image-based Barcode Detection	Industrial Products	94.5%	Limited to structured environments
Sriborrirak (2018)	Image Processing	Image Processing	93.2%	Sensitive to lighting conditions
Suriyaporn (2018)	Image-based Recognition	Banknotes	95.0%	Background noise affects accuracy
Proposed Method (2026)	ORB + Barcode Hybrid	Labels + Banknotes	96.2%	Minor confusion in similar classes

In contrast, the proposed hybrid approach provides a balanced trade-off between accuracy, computational efficiency, and practical usability. Unlike traditional barcode-only systems, the integration of ORB feature matching enables recognition even in the absence of visible barcodes. This makes the proposed system more adaptable to real-world conditions, where object visibility and environmental factors cannot be controlled.

Summary of the Study

This study proposed an intelligent vision-based recognition system to assist visually impaired individuals in identifying product labels and Thai banknotes by integrating barcode detection and ORB feature matching. The proposed hybrid approach enhances recognition robustness by combining structured barcode decoding with feature-based object recognition in real-world environments.

Experimental results demonstrated that the system achieved an overall accuracy of 96.2%, with balanced performance reflected by a precision of 95.8%, recall of 96.4%, and F1-score of 96.1%. Confusion matrix analysis indicated that most objects were correctly classified, with only minor misclassifications occurring between visually similar banknote denominations. The system also achieved an average processing time of 1.8 seconds, supporting near real-time performance on mobile devices.

User evaluation with 30 visually impaired participants showed high task success rates, with improved performance observed among trained users. This highlights the importance of usability and user familiarity in assistive technology adoption.

Overall, the findings demonstrate that the proposed system provides a reliable, efficient, and practical solution for real-world assistive applications, contributing to enhanced accessibility and supporting independent living for visually impaired individuals in a smart ageing society.

Discussions

The experimental results demonstrate that the proposed intelligent vision system achieves consistently high performance across multiple dimensions, including accuracy, robustness, and usability. The system attained an overall accuracy of 96.2%, confirming the effectiveness of integrating ORB feature matching with barcode detection for real-world assistive applications.

From a technical perspective, the balanced precision (95.8%) and recall (96.4%) indicate that the system effectively minimizes both false positives and false negatives, which is critical in assistive contexts where recognition errors can directly affect user trust. Confusion matrix analysis further shows that most misclassifications occur between visually similar classes, particularly high-denomination banknotes, highlighting an inherent limitation of feature-based recognition methods when discriminative features are insufficient.

Compared with existing approaches, the proposed system offers a balanced trade-off between accuracy and computational efficiency. Barcode-based systems (Jetjarurat, 2013; Chuchuay, 2017) are reliable but depend on barcode visibility, while feature-based methods such as SIFT (Lowe, 2004) and SURF (Bay et al., 2008) provide robustness at higher computational cost. Deep learning models, including YOLO (Redmon et al., 2016) and ResNet (He et al., 2016), achieve high accuracy but require substantial computational resources and large-scale datasets. The proposed hybrid approach effectively bridges this gap by delivering competitive accuracy with near real-time performance on mobile devices. In terms of usability, the user evaluation highlights the importance of user familiarity. Trained participants achieved significantly higher task success rates than untrained users, consistent with prior studies (Suriyaporn, 2018; Sriborrirak, 2018), which emphasize the role of interaction design and learning curve in assistive technology adoption. The system was effectively used by both totally blind and low-vision participants, indicating that the interface design supports diverse user needs.

A key contribution of this study is the integration of multiple recognition techniques within a unified system capable of handling both product labels and banknotes. Unlike prior work focusing on single-task solutions, this approach better reflects real-world scenarios in which users must identify diverse object types in daily life.

Despite these promising results, several limitations remain. System performance may degrade under extreme lighting conditions or severe occlusion, and reliance on predefined datasets may limit generalization to unseen objects. Future work could explore lightweight deep learning models to enhance adaptability while preserving real-time performance.

Overall, this study demonstrates that combining classical computer vision techniques with application-specific design provides a practical, efficient, and user-centered solution for mobile assistive systems, with strong potential to enhance accessibility and support independent living for visually impaired users.

Research Contributions

This study provides five key contributions to the field of assistive technology and computer vision: (1) Hybrid Recognition Framework: a novel integration of ORB feature matching and barcode detection that enhances recognition accuracy and robustness in real-world environments; (2) Multi-Object Assistive System: a unified system capable of recognizing both product labels and Thai banknotes, addressing practical daily needs of visually impaired users; (3) Real-Time Mobile Performance: achieves high accuracy (96.2%) with near real-time processing (~1.80 seconds), making it suitable for mobile deployment; (4) User-Centered Validation: demonstrates improved usability and task performance through empirical evaluation with visually impaired participants; and (5) Smart Ageing Assistive Impact: supports independent living and enhances accessibility through real-time audio-assisted recognition, aligning with smart ageing society goals.

Recommendations

Future research may consider the following directions:

1. Integration of lightweight deep learning-based object detection methods to further enhance recognition robustness under complex conditions.
2. Expansion of the dataset to include a broader range of consumer products and more diverse environmental variations.
3. Development of a fully functional mobile application platform to improve accessibility, usability, and real-world deployment.
4. Integration with wearable assistive devices, such as smart glasses, to enable hands-free interaction and continuous user support.

Limitations of the Study

This study has several limitations. The dataset used in the experiments was relatively limited in terms of product diversity and environmental variability. In addition, system evaluation was primarily conducted in controlled indoor environments, which may not fully reflect real-world conditions. Future research should consider larger-scale datasets and more diverse real-world scenarios to further validate and generalize the robustness of the proposed system.

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